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Improving Wind Power Forecasting Technology Using Multiple Technologies

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With the growing energy demand and climate change, wind power is considered a promising renewable energy solution. However, the inherent fluctuations and intermittency of wind generation affect grid integration. Therefore, wind power forecasting and related data decomposition methods need to be reviewed to categorize them by factors, including model architecture. Precise wind power prediction requires a systematic review of the complex interplay between high-fidelity sensor data, appropriate decomposition methods, and advanced model architectures. By exploring the evolution of wind power prediction and categorizing it into statistical, physical, and combined techniques, we compared deep learning models (e.g., convolutional neural networks, long short-term memory, and transformers) to enhance the accuracy of sensor-data-derived power generation prediction. The results of this study serve as a guide for engineers and researchers in developing the next-generation sensors and supervisory control and data acquisition systems to collect the specific, high-resolution data streams required by modern combinatorial forecasting models.

1. Introduction

Clean and renewable energy sources have become inevitable as technology advances and environmental awareness increases. Wind energy, as a clean energy source, provides a solution to meet the increasing energy demand. The scale of installed wind power has grown markedly recently, with the total amount of installed wind energy farms worldwide having increased almost tenfold in a decade.[(1)] However, the variations and unpredictability of wind energy pose a challenge to the stable generation of power. Therefore, precise wind power prediction is essential to minimize forecasting uncertainty.

Wind power prediction relies on historical generation data, wind speed, topography, numerical weather predictions (NWPs), and unit operating conditions. The methods are

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categorized by forecast time or model structure,[2] with forecast time being the most frequently used criterion. On the basis of the criteria, forecasting models are divided into ultrashort, short, and long-term types.[3] Ultrashort-term forecasts provide a prediction several minutes to hours ahead using minute-level data; short-term forecasts are made 48 to 72 h in advance mainly using the NWP model and hourly data; medium-term forecasts are made one week to a year in advance using daily data; and long-term forecasts based on yearly data are used in the feasibility study of wind farms to predict power generation using turbine power curves.[4] Forecasting results are used for power grid maintenance, dispatch, and planning wind optimal selection (Fig. 1).

When classified by structure, the models fall into physical, statistical, and combined types. In these models, appropriate data must be collected and analyzed. We investigated wind power prediction techniques to categorize them by forecast time and structure, and discussed the necessary data. Different methods require optimized data collection and processes for enhancing forecasting accuracy performance. Therefore, sensors and sensor technology must be developed to collect and process tailored data for each combined model by referring to the results of this study.

2. Sensor Data

Wind power prediction models require sensor data to accurately predict generated power. The data are related to atmospheric conditions and the operational status of wind turbines. The data collected by sensors used in wind power prediction models include meteorological data, (wind speed and direction, temperature, air pressure, and humidity), mechanical data, remote sensing data [light detection and ranging (LiDAR), sound detection and ranging (SODAR), and satellite imagery/weather radar], and wind turbine operational data (rotor speed and blade pitch angle, power output, vibrations, and component temperatures).

Meteorological data are the most crucial input, as wind speed and direction are the primary determinants of power output. Wind speed and direction are measured by anemometers (speed) and wind vanes (direction) at the turbine nacelle and often on nearby meteorological stations.[5,6] Since air temperature and barometric pressure affect air density, which in turn influences aerodynamic power conversion efficiency, they are important inputs of the models. Temperature and air pressure are measured using thermometers or thermocouples and barometers. Humidity data are collected by hygrometers to predict atmospheric conditions that form ice on the blades of the wind power generator.

Remote sensing data are gathered remotely to provide broader or higher-resolution atmospheric profiles.[6] LiDAR is used to measure wind speed and turbulence at various

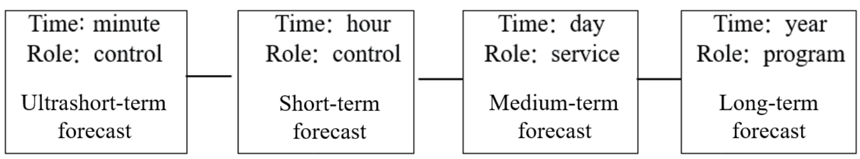

Fig. 1. Wind power forecasting methods based on forecast time.

distances and heights, offering a three-dimensional view of the wind field before it reaches the turbine.(7) SODAR is similar to LiDAR, but uses sound waves to measure wind speed and turbulence at different altitudes. To reflect regional weather patterns, cloud movement, and storm trajectories, satellite imagery data are also necessary from weather radars for short-term and medium-term forecasting. Wind turbine operational data are collected from the turbine's supervisory control and data acquisition (SCADA) system to monitor the generator's state and performance.(1) The SCADA system collects data on rotor speed and blade pitch angle using encoders and potentiometers to assess and control how the turbine reacts to the wind. The collected data are essential for modeling the power curve.(6) The power generated by the wind power generator is monitored using current and voltage transducers.(6) For condition monitoring, vibrations and component temperatures are important data in predicting and preventing a potential shutdown, which would also affect the prediction models.

To collect the data for wind power prediction models, robust, reliable, and high-frequency data logging is vital, especially for short-term predictions.

3. Data Decomposition

Data decomposition is conducted to process the collected raw data to increase the accuracy of wind power prediction.(8) Feature extraction is performed to eliminate redundant information. Through data decomposition and feature extraction, the complexity of forecasting is significantly reduced while the performance is enhanced.

3.1 Data decomposition

3.1.1 Wavelet transform (WT)

WT is applied to time series decomposition.(9) The traditional Fourier transform (FT), fast FT, and short-time FT are commonly used but cannot solve nonstationary time series problems as they maintain constant solutions at all frequencies. Therefore, WT is applied since it utilizes orthogonal wavelets in place of the sine and cosine functions of FT, thereby addressing the problem efficiently.(10) The diagram of WT is shown in Fig. 2. In the figure, *A, D, L*, and *H* denote approximation, detail, low-pass filter, and high-pass filter, respectively. The decomposition process is carried out at three levels. The approximation and detail coefficients at each level are derived using the scaling and wavelet functions defined by the selected wavelet-based Eq. (1).

$$\psi_{j,k}(t) = \frac{1}{\sqrt{2^j}}\psi\left(\frac{t - k \cdot 2^j}{2^j}\right) \tag{1}$$

Here, Ψ denotes the mother wavelet, and j and k denote scale and shift parameters, respectively.

Owing to continuous research, effective WT-based forecasting models have emerged. The combination of WT and the least-squares support vector machine (LS-SVM) with genetic

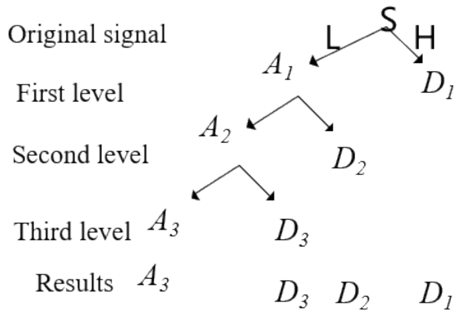

Fig. 2. Schematic diagram of WT.

algorithm (GA) optimization effectively improves the accuracy and reliability of wind power prediction approaches.(11) The combination of WT with a convolutional neural network (CNN) was proposed to decompose data to improve the forecasting accuracy.(12) Subsequently, enhanced wavelet transform (EWT) and discrete wavelet transform (DWT), variants of WT, were derived for application to the wind power field.(13) DWT is integrated with AI methods to approximate nonlinear functions to reduce the error.(14)

3.1.2 Empirical modal decomposition (EMD)

While WT excels at decomposing unorganized data, it also has limitations. For example, its nonadaptive nature necessitates the careful selection of an appropriate basis function and the number of decomposition layers to ensure its appropriateness for processing specific time series.(15) As a flexible time series decomposition method, EMD decomposes a time series into intrinsic mode functions (IMFs) and a residue using a recursive screening process.(9) Unlike WT, EMD does not require a preset basis function. Because of its finite sub-filtering nature, EMD provides benefits in managing nonstationary and nonlinear data, making it highly effective and widely applied in processing nonstationary wind power series.(16) The main features of the raw data are mined by removing the noise from the wind power signal by EMD. Therefore, combining EMD with transformers enables a better feature extraction of the EMD-transformer model due to its codec structure that is connected between the two using the attention mechanism.(17) In EMD, the convolutional attention mechanism is applied to enhance the forecasting accuracy.

The ensemble empirical modal decomposition method (EEMD) was developed by adding white noise to EMD to mitigate amplitude fluctuations in the signal. The mean of the IMF and residual components after multiple decompositions is taken as the final result, although the original data is changed by EEMD. However, the proposed EEMD-GA-backpropagation method (BP) performs better in wind speed forecasting than EMD-GA-BP since EEMD is more stable than EMD. Since EEMD decomposes and reconstructs the original data, the addition of white noise introduces errors. Therefore, complete ensemble empirical mode decomposition (CEEMD) is used to minimize noise effects and extract more meaningful components by adding paired white noise with opposite polarities into the data. [18,19] CEEMD improves the EEMD-processed time noise in the sequence, but EEMD still has computational problems. Thus, the decomposition method, named complete ensemble empirical mode decomposition with adaptive noise (CEEMADN), was developed, on the basis of EEMD.[20] The difference between CEEMADN and EEMD lies in how white noise is added. CEEMADN injects noise into the residuals from the preceding iteration rather than the raw data, enabling efficient and precise decomposition.

3.1.3 Variational modal decomposition (VMD)

The recursive nature of EMD and the lack of a clear mathematical theory make EMD effective in solving sampling sensitivity problems. VMD is developed as a complete nonrecursive decomposition method, and in decomposition, variational problems are created and solved by combining the Wiener filtering method to solve the denoising problem.[21] The Hilbert transform uses fringe spectra, and the alternating direction method is applied to solve the variational problem with constraints.[22] The principle of VMD is to convert the original data into a constrained variational problem before solving, which is expressed as[23]

$$\min\left\{\sum_{k=1}^{K}\left|\partial(t)\left[\left(\delta(t)+\frac{j}{\pi t}\right)\cdot u_{k(t)}\right]e^{\{-j\,\phi_k t\}}\right|_2^2\right\}\ \text{s.t.}\ \sum_{k=1}^{K}u_k=f\ , \tag{2}$$

where u_k denotes the kth *IMF*, $\partial(t)$ the partial derivative of the function with respect to time t, $\delta(t)$ the unit impulse response, and j imaginary units.

VMD is used in solving nonsmooth wind power series problems, and thus, various combinatorial models based on VMD are generated. For example, the combined attention convolutional and capsule network (ACCNet)-VMD is proposed for use in a decomposition method to separate the original data into decoupled sub-power-series cascade data.[24] Then, the input of ACCNet is used to make this combined model have high forecasting performance. It is also applied to separate the original data, while convolutional long short-term memory (ConvLSTM) is employed for error forecasting.[25] The results show excellent forecasting performance. Since VMD is prone to mode aliasing, the selection of hyperparameters is necessary. Wang *et al.* used the butterfly optimization algorithm (BOA) to optimize the penalty factor with a mode count in VMD so that VMD could form a comprehensive input feature vector in decomposing the unsteady wind turbine historical data. They input this vector into LSTM for forecasting, thus obtaining an enhanced forecasting effect.[26]

3.2 Feature extraction

Feature extraction is important in uncovering the relationship between input variables for dimensionality reduction. It also reduces the effect of redundant data on model training, thereby enhancing prediction efficiency.

3.2.1 Classical methods

Adaptive Kriging-subset simulation optimization (AK-SSO) is used to optimize the LSTM hyperparameters by dividing the raw wind power data into three classes through feature extraction and then predicting the mean square error of each sample based on LSTM.(27) Given the uncertainty across wind energy reserves, Cai *et al.* extracted the error characteristics of energy resources by establishing a Gaussian mix clustering model (GMCM) to improve the medium- and long-term forecasting accuracies.(28) The maximum relevance and minimum redundancy (MRMR) is a commonly used decomposition algorithm in feature extraction. MRMR combines relevance and redundancy in information theory,(29) effectively identifying both linear and nonlinear dependences between variables in the forecasting process, and thus is widely used in practice. Using MRMR, the relationships between different constituents and decomposition components are mined, and the subset with strong correlation and low redundancy is filtered, which makes the model have a good forecasting effect.(30)

3.2.2 Principal component analysis (PCA)

PCA reduces the dimensionality of the data, producing a simplified form.(31) For ultrashort-term wind speed forecasting, PCA is combined with persistence forecasting to overcome its limitation by prioritizing the coarse sampling.(32) PCA outperforms dimensionality reduction methods that rely on original and statistical features such as mean, max, min, and standard deviation.(33) Hu *et al.* reduced the dimensionality of the input information, maintaining high dimensionality, and input the processed data into an improved deep confidence network.(34) In addition to the conventional processing of redundant information in the original data, the time–frequency domain is employed to analyze and remove the redundant information. PCA combined with VMD and EMD is also used to process numerical weather forecasting (NWF).(35)

4. Forecasting Models

4.1 Physical model

The physical model represents the wind energy distribution in wind farms and converts it into output power.(36) Using a common NWF method, wind speed–power curves are drawn to investigate the correlation between historically measured power and wind speed data. As NWF has a low reliance on historical data and relationships, a large dataset is required, and the complexity of the actual data is not considered in the process. Therefore, the results of NWF deviate significantly from the actual data, so the NWF model is appropriate for long-term forecasting.

4.2 Statistical model

Statistical models process a large amount of historical data and select an appropriate forecasting method by comparing historical data with wind power outputs obtained by each method. AI algorithms are integrated to improve the performance. Statistical models are classified into classical and time series models.

4.2.1 Classical models

The most commonly used classical model is the continuum method, which is the simplest forecasting method. Its principle is to use the wind power at the current moment for forcasting. When $X_{t+\Delta t}^{(P)}$ is the wind power in the next moment, $t + \Delta t$ is the forecasting range in time, and X_t is regarded as the wind power at the current moment. Then, the following is established:[37]

$$X_{t+t}^{(p)} = X_t. \tag{3}$$

The operation of the method lacks the knowledge of the relevant data trends and rates of change, and the accuracy of forecasting decreases over a longer period. Therefore, the model is only applicable to forecasting ultrashort-term wind power.

4.2.2 Time series model

The time series model is commonly used in wind power prediction. Statistical models differ from physical models as they require historical data for analysis, while the time series model is established on the basis of the relationships between the historical data, the random error, and the forecast data. Time series models include the autoregressive (AR) model, the moving average (MA) model, and the autoregressive integrated moving average model (ARMA), which is a combination of the AR and MA models.

The AR model combines the historical data with the current data and creates a weighted combination of historical data for forecasting future wind power. The AR model simulates the instantaneous structure of wind power values, which is beneficial for short-term power prediction.[38] The AR model is mathematically expressed as

$$X_t = C + \sum_{i=1}^{P} \theta_i X_{\{t-i\}} + \epsilon_t \ , \tag{4}$$

where X_t is the value at time t, C a constant, θ_i the model coefficient for each of the first p terms, and ϵ_t noise.

In the model, autocorrelation (the degree of dependence between wind speed data at different time points) is calculated using Eq. (4).[39] This provides accurate and reliable information for short-term forecasting.

The ARMA model has been used for forecasting wind power since the 1980s. Erdem and Shi decomposed wind speed into horizontal and vertical components in accordance with the wind direction and used an ARMA model to improve the accuracy of forecasting.[40] Its typical model is

$$y_t = \delta + \sum_{i=1}^{p} \varphi_i \times y_{\{t-i\}} + \sum_{j=1}^{q} \theta_j \times e_{t-j} + e_t \,. \tag{5}$$

Although the method is simple, its adaptability is poor and unexpected problems are difficult to solve. For example, for gusts or sudden changes in wind conditions, its forecasting accuracy decreases with an increase in forecasting time. Therefore, the ARMA model is only appropriate for short-term or ultrashort-term power forecasting.

4.3 AI model

With the emergence of big data algorithms, AI models are widely used owing to their advantages in extracting features. The artificial neural network (ANN) and support vector machine (SVM) are mainly used. They uncover the latent connection between input data and target outcomes, establishing a functional model to predict wind power.[41]

4.3.1 SVM

SVM is a classification and regression method derived from statistical learning theory and follows the principle of structural risk reduction. The algorithm exhibits a robust generalization capacity with a limited amount of data, which is suited for wind power forecasting.[42] The SVM model has been developed into the proposed piecewise SVM (PSVM) and least-squares SVM (LSSVM), with a notable improvement in wind power prediction performance. The combination with SVM, PSVM, LSSVM, and other models significantly enhances the precision of wind power prediction. However, the parameters of SVM-based models are selected empirically and stochastically. Therefore, the parameters are difficult to determine. Such drawbacks necessitate GAs,[43] honey badger algorithms,[44] and fruit fly algorithms. The behavioral characteristics of animals are applied in models for the determination of parameters for wind power forecasting.

4.3.2 ANN

ANN is developed by mimicking neurons of the human brain but has a simple structure (Fig. 3).[45] Ali and Aly proposed different scenarios to train ANNs using raw time series data to ensure an ANN forecasting performance higher than those of existing models in short-term wind speed prediction.[46] Commonly used approaches include generative adversarial, radial basis function, and general regression networks.[47]

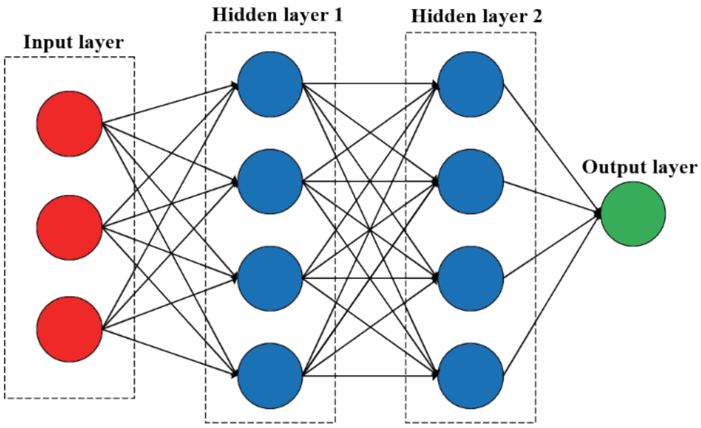

Fig. 3. (Color online) ANN structure.

4.4 Neural network model

A neural network model extracts key features and captures nonlinear relationships between data, making it appropriate for handling large-scale, high-dimensional time series. Because of its powerful parallel computing and adaptive learning capabilities, its pattern recognition and trend forecasting ability exceeds that of traditional linear models, greatly enhancing prediction performance. In wind power forecasting, traditional machine learning methods are being replaced by deep learning models.(48) Deep learning models process the spatial and structural information of the input data, especially global dependences. CNN, transformer, and autoencoder (AE) models are deep learning models.(34,49,50) Time-based deep learning models process sequence data to capture the temporal information by transmitting hidden states. LSTM and gated recycling unit (GRU) models are widely used as time-based deep learning models.(51,52)

4.4.1 CNN model

CNN models have a powerful feature extraction capability and efficiently process two-dimensional (2D) data, which makes them appropriate for wind power forecasting.(53) Figure 4 illustrates the architecture of the CNN model.

Zhang *et al.* applied CNN to wind power forecasting by building a regression model.(54) CNN demonstrates an outstanding ability in wind power forecasting, similar to its success in image processing.(55) VMD is used with CNN to decompose and extract features of meteorological data.(56) A residual neural network is integrated with CNN to extract features of wind energy to enhance forecasting accuracy.(57)

To achieve better prediction results with CNN, data enhancement, feature engineering, parameter optimization, and model integration are used. For example, VMD is used to mitigate the wind speed fluctuation series to enhance the correlation between the data and the extract complex spatial and temporal features from historical data using CNN and GRU. The combined

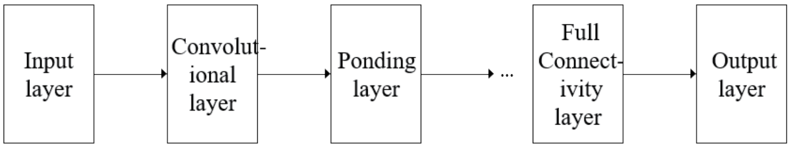

Fig. 4. CNN structure.

VMD-CNN-GRU model outperforms the other deep learning models.(57) A random forest (RF) algorithm is used to evaluate the features.(58) The RF algorithm evaluates the importance of features for more effective feature extraction. An integrated GA and PSO algorithm synergistically optimizes the network's hyperparameters and weights while effectively optimizing tuning parameters and model structure parameters.(59) After optimizing the algorithm processing the parameters and weights are used to effectively alleviate the local optimum problem, which, in turn, improves the CNN predictive power.

4.4.2 Transformer

A transformer is developed on the basis of the self-attention mechanism. Owing to its multiple attention mechanisms, the transformer is widely used in natural language processing.(57) The transformer model comprises an encoder–decoder structure, where both parts include multiple attention and normalization layers.(60) Because of its own mechanism, the transformer can effectively capture the relationship between variables and performs well in tasks such as wind power forecasting.

The transformer's self-attention mechanism enables global associations in sequences, allowing the model to focus on all locations simultaneously in processing sequence data without step-by-step processing as in RNNs and LSTMs. Its own mechanism supports the parallel processing of information and enhances the processing capability of the model.(61) The transformer's mechanism expands the receptive field and enhances generalization, leading to more accurate forecasts. With its powerful modeling capability, the transformer sequentially processes data such as wind speed and power on different time scales through parallel computing.(62) With the tree-structured Parzen estimator (TPE) and time fusion transformer (TFT) framework, wind power forecasting can be automated, which is efficient for multiscale wind power prediction.(63)

In wind power prediction, future values are predicted without converting the input to the output sequence format. In this case, the decoder of the transformer model is not used, and only the output of the encoder is used to extract and transmit features to the fully connected layer to retrieve the final output.(64) To strengthen the transformer's prediction performance, the comparative learning method is used in the self-supervised learning of the feature representation of wind power sequences and a wind power forecasting framework, including prestage regression.(65,66) The framework is applied to various network architectures to significantly increase the reliability and accuracy of the prediction. In contrast, the improved complete ensemble empirical mode decomposition with adaptive noise approach (ICEEMDAN) is applied to break down the raw wind speed series, send the decomposed components into the transformer for forecasting, and combine the results. The transformer combined with ICEEMDAN has significantly improved forecasting performance.

4.4.3 AE

AE consists of an encoder and a decoder, which learn the high-dimensional features of wind power data, map them onto a compact representation, and reconstruct them so as to reflect the intrinsic laws of wind power for wind power prediction. Figure 5 illustrates the architecture of AE.

Tasnim *et al.* proposed a structured sparse AE (SAE) model.(67) In training, the model optimizes the initial connection weights of the deep network using a specific loss function. Then, an output layer is added to the structure of the stacked AE, and the weights of the whole network are fine-tuned using the BP algorithm. In addition, PSO is integrated to optimize the learning rate of the encoder. The approach shows a forecasting accuracy higher than those of traditional BP neural networks and SVMs. Stacked denoising autoencoders (SDAEs) are used to simulate the spatial correlation and interdependence between wind fields, thus improving the accuracy of numerical weather forecasting.(68)

4.4.4 LSTM

LSTM is an improved RNN whose core structure incorporates the forgetting, input, and output gates based on the traditional RNN (Fig. 6). Cheng *et al.* significantly enhanced the long-term forecasting performance of wind farms by LSTM.(69) For short-term power prediction, methods built on LSTM and recurrent neural networks are extensively adopted owing to their excellent performance in time-series forecasting. Since the forecasting accuracy is significantly improved, PSO and PSO-BP hybrid models present excellent 4, 24, and 72 h wind forecasting.(70) In addition to improving the LSTM model, different models are combined to boost prediction performance.

Lu *et al.* proposed a forecasting approach combining CNN and LSTM based on historical data.(71) They combined forecasting models using screened meteorological key factors through

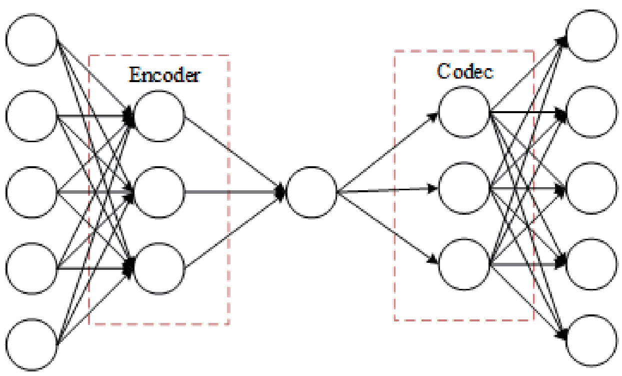

Fig. 5. (Color online) AE structure.

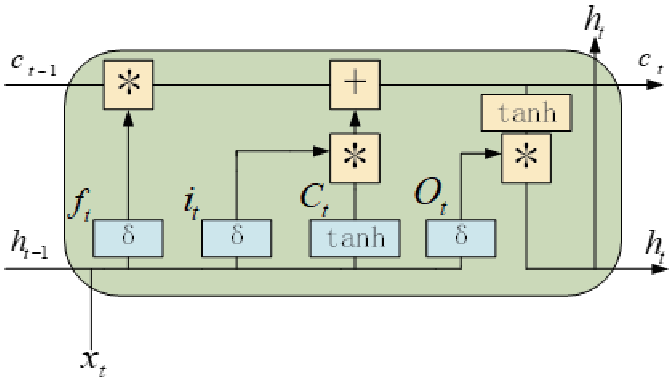

Fig. 6. (Color online) LSTM structure.

data decomposition, model integration, and optimization strategy. The CNN-LSTM forecasting forecasts wind power on the following day with high accuracy and reliability.(72) An improved Bayesian neural network model, which incorporates a Bayesian network into LSTM, captures long-term dependences. The model processes historical wind power data and combines a temporal convolutional network (TCN) through dimensionality reduction, enabling high accuracy in wind power forecasting with high volatility.

4.4.5 GRU

GRU is an improved variant of RNN.(73) In the unit structure of GRU, reset and update gates replace the three-gate unit structure in LSTM (Fig. 7). In GRU, the update gate controls the extent to which past information is retained in the present state, while the reset gate regulates the relevance of the current information to the past information. GRU effectively retains key input information by using the update and reset gates to gradually discard irrelevant time. The isolation forest (IF) algorithm removes the anomalous data after detection, and on the basis of that, GRU performs better than LSTM.(73) Niu *et al.* used GRU to incorporate the attention mechanism, which embedded the associated tasks in different forecasting processes to enhance prediction effectiveness.(74) Chi and Yang used the bi-directional GRU (BiGRU) to improve forecasting performance.(75) BiGRU captures potential relationships between features to extract time series contextual features. The predictive performance of the BiGRU model outperforms traditional LSTM and GRU. GRU has a more concise structure and requires fewer training parameters than LSTM, which makes it efficient in forecasting. However, since the forecasting output of GRU relies on the information at the current moment, the model tends to ignore the previous important information.(22)

4.5. Combined models

Because wind power is inherently random and volatile, a single model cannot achieve satisfactory predictions. Hybrid approaches leverage the strengths of different models to greatly enhance predictive performance. Four combined forecasting approaches are widely used,

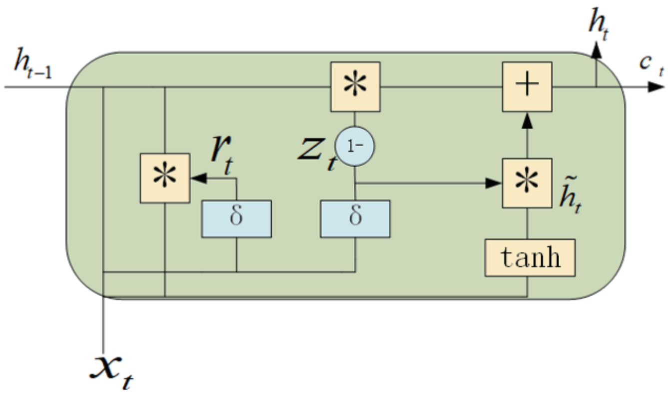

Fig. 7. (Color online) GRU structure.

including the multimodel weighting, data preprocessing, error correction, and optimization algorithm models.

4.5.1 Multimodel weighting model

The multimodel weighting model combines the weights of different forecasting models and the results of each model. The architecture is depicted in Fig. 8. In the multimodel weighting model, the SVM and radial basis function neural network (RBFNN),(76) SVM, LSTM, ARMA,(77) BPNN, and Elman neural network (ENN) are usually combined to simulate environmental changes and wind speed characteristics in different periods. To further improve forecasting performance, the internal structure of the model is optimized using a multifeature approach.

For example, wind power prediction is forecasted using a nonparametric lower-bound estimation framework with LSTM.(78,79) The proposed method achieves results superior to those of standard RNNs. The multimodel weighting scheme markedly improves forecasting robustness and accuracy by leveraging raw features as inputs to the prediction framework. The deep belief network (DBN) is used for short-term wind speed forecasting based on the values forecasted by the RF algorithm. The model dynamically updates the weights using the weight voting approach (WVA) to improve forecasting accuracy.

The multimodel weighting model relies on a weight updating mechanism to adjust the weights of submodels. Therefore, high degrees of flexibility and adaptability are ensured, and excellent performance in forecasting accuracy is obtained. However, the computational efficiency of the method is low and the scope of application is limited, which restricts its application in a wider range of scenarios.

4.5.2 Data preprocessing

Data preprocessing is important for modeling and data mining. Data preprocessing is also conducted to process missing or noisy data. Through data preprocessing, the raw data is decomposed into multiple subsequences so that a model can predict the subsequences. Figure 9 shows the implementation process of the combined forecasting method.(80,81)

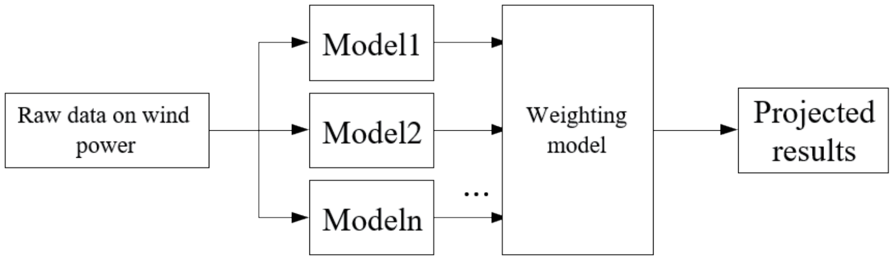

Fig. 8. Schematic diagram of multimodel weighting model.

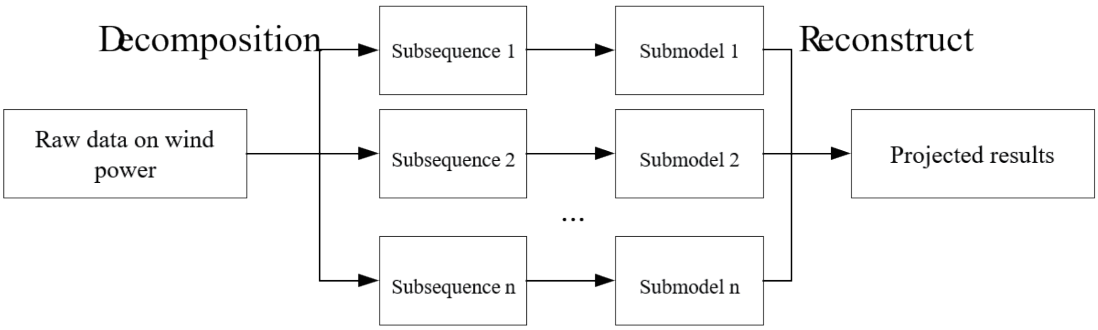

Fig. 9. (Color online) Schematic diagram of data preprocessing method.

For signal decomposition, EMD, VMD, or WT is used to decompose the raw data.[82] A combined model makes forecasts on the basis of the decomposed data. For example, Moreno *et al.* combined VMD with singular spectral analysis (SSA) and LSTM to build a VMD-SSA-LSTM data preprocessing model for short-term wind prediction.[83] The model reduced the forecasting error, especially in multistep forecasting. A novel hybrid model combining WT, feature selection (FS), crow search algorithm (CSA), and LSTM is used for short-term wind speed prediction.[84] By comparing different forecasting methods, the model with data preprocessing can enhance forecasting accuracy and performance. However, the seasonal variation in wind speed, which requires the error correction method and optimization algorithm, has not been considered.

4.5.3 Optimizing models

In the combined forecasting method based on the optimization method, parameters need to be determined for forecasting. Figure 10 illustrates the optimization process of a model. Wind power forecasting models require numerous parameters. Therefore, it is important to adjust the parameters. Although traditional optimization algorithms are widely used for wind power prediction, they lack the capability of determining and optimizing parameters effectively. The CNN-LSTM model adjusts network parameters through training to optimize the parameters.[85] Traditional optimization algorithms easily fall into local extreme values. To solve this problem, CSA and the extreme learning machine (ELM) are integrated, leveraging CSA's optimization capability and ELM's output layer weights to enhance the precision of interval forecasting and wind power prediction.

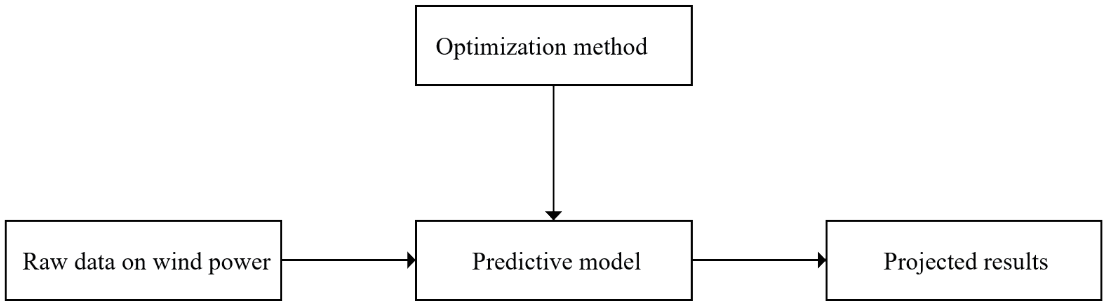

Fig. 10. (Color online) Optimization process.

To solve complex problems, intelligent optimization algorithms are used. The intelligent optimization algorithms are divided into single-solution and multiple-solution algorithms in accordance with the number of solutions in each iteration.(81) Multisolution algorithms are extensively applied in wind power prediction. The South American Coati optimization algorithm (COA) is constructed on the basis of a COA-CNN-LSTM model. The model determines the initial parameters of COA and iteratively optimizes them, enabling accurate wind power forecasting.(86,87) An improved seagull optimization algorithm (ISOA) optimizes the parameters of LSTM, with the ISOA algorithm showing a higher forecasting performance than the LSTM model.(88) Although the intelligent optimization algorithm has fewer generalization errors and a higher convergence speed than the traditional algorithm, it cannot guarantee the optimal solution.

4.5.4 Error correction methods

The combined forecasting error-correction–driven approach mitigates the effect of forecasting errors by post-processing the data. In this method, combined forecasting methods are used to reduce forecasting errors and improve forecasting accuracy on the basis of the results of different models. The error correction process is depicted in Fig. 11.

The decomposition model can accumulate errors, which necessitate error correction methods. Reconstructed forecasting results are compared with original results to reduce errors and improve forecasting accuracy.(89) By applying an error correction approach, relevant error metrics are identified.(90) The gradient boosting decision tree (GBDT) is usually used to determine error indicators, while extreme gradient boosting (XGBoost) is used for error correction. In their processes, the initial forecasted values are summed and compared and validated using real wind farm data to correct errors. XGBoost shows the best error reduction. Sometimes, the VMD method is used to decompose errors and erratic sequences into stochastic and trend components, and group them to analyze the volatility of the components. Different error correction approaches are utilized to enhance short-term wind power prediction accuracy. The error correction method has a lower computational efficiency than combined methods, although the model with the method shows enhanced forecasting accuracy.(91)

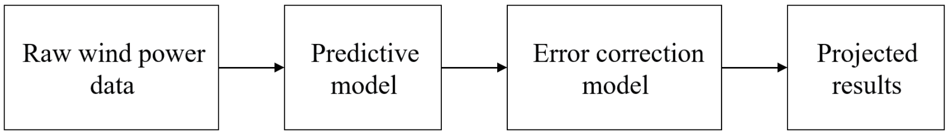

Fig. 11. (Color online) Error correction process.

5. Conclusions

In wind power prediction, deep learning is widely used. Because of the continuous development of deep learning methods, wind power forecasting accuracy and speed have been significantly improved. Recently, innovative models based on time series data and various methods, such as the transformer, have been introduced to wind power prediction. Using data and various methods, combined models are developed for a more accurate wind power forecasting than a single model. Despite the advancement of technology, challenges remain in accurate forecasting. At the same time, it is necessary to consider the operating conditions and the needs of individual wind farms in wind power forecasting. Diverse forecasting models should be developed to strengthen the efficiency and effectiveness of wind energy production.

By reviewing and comparing the current state of wind power forecasting and focusing on advanced data decomposition, deep learning algorithms, and combinatorial models, the results underscore that the maximization of prediction accuracy depends on the quality and type of sensor data. We highlighted that data inputs originate from diverse physical sensors, including anemometers, LiDAR, thermocouples, and the turbine's SCADA system, which collect critical meteorological, remote sensing, and operational parameters. The sophisticated deep learning and signal processing techniques reviewed are advanced methods for extracting meaningful features from sensor data.

Further research is necessary to focus on model refinement and the development of specialized sensors and data acquisition for multidimensional data streams, high-frequency temporal data, ultrashort-term forecasts, or specific atmospheric profiles for anti-icing prediction. Ultimately, the performance of advanced forecasting models is determined by the sensor technology. The results of this study serve as a reference, linking the demands of wind power analytics to the development of robust and precise sensing and materials.

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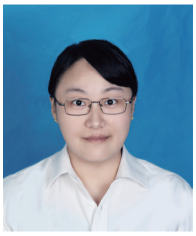

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